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# Dementia Demystified: A Survey of Datasets, Models and Assistive Technologies

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**Abstract:**
Dementia is a progressive neurological disorder that significantly impairs memory, cognition and daily functioning by affecting millions of individuals worldwide. As the global population ages there is a huge demand for early diagnosis, effective management and supportive care solutions continues to rise. This survey provides a comprehensive overview of dementia through begin with an exploration of its clinical background and common symptoms. We then examine a broad range of datasets that have been utilized in dementia related research by highlighting their characteristics, accessibility and relevance. The paper also reviews various computational and machine learning models developed for the detection and classification of dementia by discussing their methodologies along with performance and limitations. Also the paper explore a variety of assistive technologies designed to support individuals with dementia in their daily lives by including cognitive aids, monitoring systems and user friendly interfaces. By bridging clinical insights with technological advances this survey aims to guide researchers, developers and healthcare professionals toward more effective and integrated solutions for dementia care.

**Keywords:** Dementia detection, Computational models, Assistive Technologies, Datasets

## 1. Introduction

Dementia represents a growing global health concern which is characterized by a progressive decline in cognitive function that interferes with daily life and independence. As populations age the prevalence of dementia related disorders such as Alzheimers disease, vascular dementia and Lewy body dementia continues to rise and placing significant burdens on healthcare systems. Timely diagnosis and effective intervention are essential for managing symptoms and improving quality of life also early detection remains a challenge due to the subtle onset and complex nature of cognitive decline. Researchers have increasingly turned to data driven approaches and technological innovations to enhance understanding, diagnosis and care. A wide array of datasets ranging from neuroimaging and clinical records to speech and behavioural data has been developed to facilitate Machine Learning (ML) and Artificial Intelligence (AI) based detection methods. Alongside these diagnostic tools and assistive technologies from wearable devices to intelligent home systems are being designed to support individuals living with dementia and to aid caregivers in monitoring and intervention.

This survey aims to provide a comprehensive overview of the current landscape in dementia research by focusing on publicly available datasets, computing models and emerging assistive technologies. By synthesizing existing work across these domains we seek to highlight trends, identify research gaps and outline future directions that could accelerate progress in dementia care and diagnostics.

## 2. About Dementia

The paper [1] provides a thorough clinical overview with an emphasis on evidence based guidelines for identifying and managing dementia including Alzheimers and other neurodegenerative illnesses. Here the authors address pharmaceutical and non-pharmacological treatments and diagnostic techniques including neuroimaging and cognitive testing by stressing the value of a multidisciplinary approach without the use of computer models or datasets. The author [2] does a thorough medical reference devoted to the clinical diagnosis and management of dementia. It stays away from computational models or datasets and is meant to be a clinical and educational tool. By categorizing problems as cortical or subcortical the authors highlight a neurologic approach that differentiates between treatable and incurable forms of dementia by including Alzheimers, vascular, frontotemporal and prion illnesses. The genetic foundation of dementias including Alzheimers disease and frontotemporal dementia is examined in the paper [3]. The study focuses on medical and genetic research with known genetic variants associated with these disorders are summarized. These include autosomal dominant mutations in genes such as APP, PSEN1, PSEN2, MAPT, GRN and C9ORF72. The study underscores the relevance of genetic factors in dementia and stresses the value of genetic testing and counselling in clinical practice. The thorough clinical handbook Practical Dementia Care [4] focuses on the medical and psychiatric management of dementia. Instead of using algorithms from ML or datasets it aims to give physicians and caregivers evidence based and useful practices. The authors offer a methodical strategy that addresses diagnosis, therapy and neuropsychiatric symptom management. The book uses expert opinion and clinical research to support best practices even if it lacks rigorous statistical analysis. The author [5] uses data from a prospective and community based cohort of 15,043 participants among them 26.9% Black, 55.1% female and 30.8% APOE ε4 carriers to investigate dementia epidemiology in the United States. The study focuses on epidemiology and public health to estimate the lifetime risk of dementia from the ages of 55 to 95 using statistical analysis while taking mortality into account as a competing risk. A 42% lifetime risk is reported with greater rates among women, Black people and APOE ε4 carriers.

## 3. Various models and datasets used for dementia detection

A Modified Capsule Network (M-CapNet) is suggested by the study [6] as a means of diagnosing Alzheimer's disease (AD) early. The model categorizes people as either demented or non-demented using the OASIS dataset which contains 373 samples and 15 features apiece. By adding an extra feature extraction layer Singular Value Decomposition (SVD) for transformation matrices and the Squash activation function M-CapNet compensates for the loss of spatial information in conventional CNNs. These developments are intended to enhance classification performance and better retain spatial hierarchies.

A deep learning model that combines a Convolutional Neural Network (CNN), Siamese network and ensemble classifier to classify Alzheimers disease stages using MR images is presented in the paper [7]. To resolve class imbalance the authors used the Synthetic Minority Over sampling Technique (SMOTE) on the Kaggle Alzheimers Disease dataset. DEMNET outperformed current models with 95.23% accuracy, 97% AUC and a Cohen's Kappa of 0.93. These findings highlight DEMNETs potential for clinical application as well as its efficacy in early AD identification. The usefulness of seven ML algorithms for dementia diagnosis is assessed in the paper [8]. The study analyzes Support Vector Machine (SVM), Logistic Regression (LR), Artificial Neural Network (ANN), Naive Bayes (NB), Decision Tree (DT), Random Forest (RF) and K-Nearest Neighbor (KNN) using datasets from OASIS, ADNI and Dementia Bank (DBANK). SVM and RF consistently performed better than the other models. SVMs robustness was demonstrated by its 93% accuracy on the OASIS dataset. The potential of SVM and RF in clinical dementia classification tasks is highlighted by this comparative investigation.

The paper [9] investigates the efficacy of various ML algorithms in classifying dementia stages using clinical and demographic data. The study utilized the Alzheimers Disease Neuroimaging Initiative (ADNI) dataset focusing on the Clinical Dementia Rating Scale Sum of Boxes (CDR-SB) scores along with demographic variables such as age, education, gender, ethnicity, race, marital status and examination site. The authors applied five ML algorithms namely SVM, KNN, NB, C4.5 Decision Tree and RIPPER to predict dementia status. Performance evaluation was conducted using metrics including accuracy, sensitivity, specificity, F-measure and Receiver Operating Characteristic (ROC) area. Among these C4.5 achieved the highest accuracy of 89.7% with sensitivity and specificity rates of 89.7% and 93.2% respectively. Naïve Bayes and RIPPER also demonstrated competitive performance with accuracy rates of 88.4% and 89.0% respectively. These findings suggest that ML models based on neuropsychological assessments and demographic data can effectively classify dementia stages offering a less invasive approach to clinical diagnosis. Using the OASIS dataset the paper[10] investigates the efficacy of many ML techniques. Using three feature sets the complete set, features chosen by LASSO and features chosen by the Chi-square test the authors assessed nine classifiers including SVM, KNN, LR, NB, RF, DT, AB, GB and ET. Using the entire feature set SVM had the highest accuracy of any model at 96.77% but KNN and LR also did well. This study demonstrates how SVM and other models may be used to accurately predict dementia based on clinical imaging data.

A thorough investigation into dementia classification utilizing both imaging and numerical data is presented in the work [11]. The authors used the OASIS longitudinal dataset which included 373 MRI sessions from 150 subjects between the ages of 60 to 96 and the Alzheimers MRI dataset including 6400 segmented images. They trained 15 ML models with and without hyperparameter

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adjustments. The accuracy, precision, recall, F1-score and ROC curves were used to assess the model performance with 98.31% precision and 95.54% accuracy. Naïve Bayes produced the best results demonstrating the value of parameter optimization in multimodal dementia detection. Using the ADReSS challenge dataset the authors[12] explores deep transfer learning models for Alzheimers classification. For regression and classification tasks a pretrained model such as MobileNet, YAMNet (audio), Mockingjay (speech), BERT and Longformer (text) were optimized. Metrics including accuracy, precision, recall, F1-score and RMSE were used to assess these models on the test set after they had been trained on the ADReSS training set. With an accuracy of up to 89.58% text based models particularly Longformer performed better than audio based ones. The outcomes demonstrate how well text features and transfer learning work for AD detection. Multi-task transfer learning for dementia detection from spontaneous speech is examined in the work [13] which is presented at ESANN 2025. To extract characteristics from conversational data the study makes use of pre-trained models namely MobileNet (image), YAMNet (audio), Mockingjay (speech), and BERT (text). It contrasts two methods of learning namely Direct multi-task learning which involves learning activities all at once and Intermediate multi-task learning involves learning tasks sequentially with shared representations. The collection focuses on grammatical and auditory aspects includes spontaneous speech from both healthy people and dementia sufferers. The study emphasizes the transfer of learning may improve the categorization of dementia from unstructured conversation.

A lightweight CNN called EEGConvNeXt is presented in the paper [14] intended to categorize Alzheimers disease (AD), frontotemporal dementia (FTD) and healthy controls (HC) using EEG data. In order to handle EEG power spectrograms the model uses a transformer like CNN architecture with four stages such as stem, main model, downsampling and output stem. Its architecture captures intricate EEG signals with a focus on computing efficiency. An EEG dataset with three classes AD, FTD and HC that is publicly accessible is used in the study. Automated dementia identification from EEG signals is successfully accomplished by EEGConvNeXt. In order to guarantee secure dementia classification the paper[15] suggests a novel method that combines Federated Learning (FL) with quantum inspired encryption. A CNN is trained decentralized using the OASIS MRI dataset for protecting patient privacy by storing data locally. The system securely transfers model weights between clients and the central server using encryption methods modelled after Quantum Key Distribution (QKD). This facilitates cross institutional training collaboration while improving data security during aggregation. The framework's efficacy in safe privacy preserving dementia detection is demonstrated by experimental results which show an accuracy of 77.77%.

A novel approach to dementia classification is presented in the publication [16]. This method involves converting EEG signals from deep brain regions into image forms for deep learning. Two EEG datasets are used in the study such as IITD AIIA (64 channels with AD, MCI and healthy controls) and BrainLat (128 channels with AD, FTD and healthy controls). Continuous Wavelet Transform (CWT) is used to turn sLORETA extracted scout time series from the thalamus, amygdala and hippocampal regions into pictures. DL models like DenseNet, ResNet and EfficientNet are fed these photos in order to classify them. This method improves the models ability to differentiate between different kinds of dementia by efficiently capturing temporal and spatial data from EEG. The paper [17] uses the ADReSS 2020 challenge dataset to investigate the use of acoustic speech features for differentiating Alzheimers disease from Healthy Controls. Instead of segmenting speech as in previous studies the researchers retrieved features from full recordings and participants performed an image description assignment that featured a kitchen scene. The Extreme Minimal Learning Machine (EMLM), Ridge linear regression and Linear Support Vector Machine (L-SVM) are among the models that are employed. Feature importance is determined by the models outputs. Ridge regression when validated using a Leave One Subject Out (LOSO) method has the maximum accuracy of 87.8%. Accuracy and computing efficiency are prioritized in this method for classifying dementia based on speech.

Several machine learning models for dementia classification are examined in the work [18]. To distinguish between those with and without dementia the authors used SVM, RF and KNN on the OASIS dataset which includes 373 MRI scans from 150 subjects between the ages of 60 and 96. F1-score, recall, accuracy and precision were used to assess the model's performance. Out of all of them, RF had the best results with 94.39% accuracy and sensitivity. A ML based method for classifying dementia using both numerical and picture data is presented in the paper[19]. Two datasets are used in the study namely the Open Access Series of Imaging Studies (OASIS) longitudinal dataset which includes 373 MRI sessions from 150 subjects aged 60 to 96 and an Alzheimers MRI image dataset which consists of 6400 images divided into four classes namely no dementia, very mild dementia, mild dementia and moderate dementia. Logistic Regression (LR), Naïve Bayes (NB), KNN, RF, Adaptive Boosting (AdaBoost), Gradient Boosting (GB), XGBoost and SVM are among the 15 ML models that the authors use both with and without hyperparameter adjustment. A convolutional neural network (CNN) model for dementia classification using EEG signals is presented in the study [20]. A max pooling layer and a dropout layer for generalization, two convolutional layers for feature extraction and two fully connected layers with a softmax layer for classification are all included in the model. Dataset-A (Alzheimer's disease, moderate cognitive impairment and normal control) and Dataset-B (identical circumstances) are two publicly accessible multiclass EEG datasets used in this work.

The use of linguistic features from speech transcripts for early dementia diagnosis is examined in the paper [21]. The study makes use of preprocessing techniques like stemming, tokenization, stopword removal and the extraction of features like document length, word frequency and hesitation words using the DementiaBank Pitt corpus which consists of 1541 transcribed speech samples (586 from individuals with dementia and 955 from healthy controls). Semantic information is captured via word embeddings such as Universal Sentence Encoder, GloVe and Word2Vec then classification is done using ML methods like SVM, KNN, RF and ANN.

Eye-AD is a deep learning framework for identifying Early onset Alzheimers Disease (EOAD) and Mild Cognitive Impairment (MCI) using Optical Coherence Tomography Angiography (OCTA) images of the retinal microvasculature is presented in the paper[22]. Eye-AD analyzes intra and inter instance interactions in retinal layers using a multilevel graph model. Around 5751 OCTA pictures from 1671 people in multiple centers were used to train and assess the model. External validation produced Area Under Curve (AUC) of 0.8037 for MCI and 0.9007 for EOAD while Eye-AD obtained an AUC of 0.8630 for MCI and 0.9355 for EOAD detection in internal testing. The paper[23] introduce a multimodal dataset collected from 20 people living with dementia over up to 60 days comprising over 2300 hours of sensor data and 169 manually annotated agitation episodes. Using physiological signals such as electrodermal activity, heart rate and accelerometry from Empatica E4 wristbands the author benchmark several ML models for agitation detection. Their baseline models achieved up to 83.3% F1-score with Transformer based models showing superior performance in follow up studies reaching an AUC ROC of 0.91. This dataset and benchmark set a new standard for developing AI driven monitoring systems in dementia care environments. The paper [24] presented anonymises speaker embeddings while maintaining their efficacy in dementia detection. Their method circumvents the necessity for a dementia classifier by employing mutual information guided shuffling to separate dementia relevant prosodic traits from speaker identification. Using the ADReSS dataset the model reduced speaker recognition to just 0.01% while maintaining privacy and achieving a 74% F1-score in dementia detection. Similar results are obtained on the ADReSSo(Alzheimer's Dementia Recognition through Spontaneous Speech (audio only)) dataset with a speaker recognition F1 of 0.66% and a verification Equal Error Rate of 0.01%. There is no discernible loss of quality because the technique preserves the naturalness of the synthesized speech. This paper offers a robust framework for prosody based dementia screening that takes privacy into consideration.

**Table 1: Performance analysis of the models along with dataset and accuracies.**

| SN | AUTHOR'S NAME | TECHNIQUE | MODES / Datasets | PERFORMANCE ANALYSIS |
|---|---|---|---|---|
| 1 | Suriya Murugan et. al., [2] | Deep Learning DEMNET | Magnetic Resonance (MR) Image. | Accuracy: 95.23%, AUC (Area Under Curve): 97%, Cohen's Kappa: 0.93 |
| 2 | Yunus Miah et. al., [3] | Machine Learning | OASIS (Open Access Series of Imaging Studies), ADNI (Alzheimer's Disease Neuroimaging Initiative), DBANK (Dementia Bank) | **OASIS Dataset:** *SVM:* 93% accuracy, *Random Forest:* 84.2% accuracy. **ADNI Dataset:** *SVM:* 93% accuracy, *Random Forest:* 84.2% accuracy. **DBANK Dataset:** *SVM:* 68.4% accuracy, *Random Forest:* 68.4% accuracy, *Naive Bayes:* 63.1% accuracy |
| 3 | Rabah AlShboul et. al., [4] | Machine Learning | ADNI dataset, OASIS dataset, Demographic data, Clinical Data | *C4.5 Decision Tree:* Accuracy: 89.7%, Sensitivity: 89.7%, Specificity: 93.2%, F-Measure: 89.8%; *Naïve Bayes:* Accuracy: 88.4% , |

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|---|---|---|---|---|
| | | | | Sensitivity: 88.4%, Specificity: 91.7%, F-Measure: 88.4%; *RIPPER:* Accuracy: 89.0%, Sensitivity: 89.0%, Specificity: 92.3%, F-Measure: 89.1%; *SVM (Linear):* Accuracy: 74.7%, Sensitivity: 74.7%, Specificity: 82.3%, F-Measure: 74.8%; *KNN (k=5):* Accuracy: 76.8%, Sensitivity: 76.8%, Specificity: 83.9%, F-Measure: 76.7%. |
| 4 | Sara Dhakal et. al., [5] | Machine Learning | OASIS, LASSO, Chi-square tests | *SVM:* Accuracy: 96.77%, Precision : 100%, Recall : 87.93%, F1-Score : 93.57% *KNN:* Accuracy: 95.16%, Precision : 100%, Recall : 100%, F1-Score : 94.54% *Chi-square :* Accuracy : 94.35%, Precision : 100%, Recall : 87.93%, F1-Score : 93.57% |
| 5 | Swati Gupta et. al., [6] | Machine Learning | Numerical Dataset (OASIS Longitudinal Dataset), Image Dataset (Alzheimer's MRI Dataset), | **Numerical Dataset (OASIS):** *Naïve Bayes:* accuracy : 95.54%, precision : 98.31%, recall : 93.55%, F1-score : 95.87% ; *SVM:* accuracy : 94.64%, precision : 98.31%, recall : 92.06%, F1-score : 95.08%. *Logistic Regression (LR) :* accuracy : 94.64%, precision : 98.31%, recall : 92.06%, F1-score : 95.08%; KNN, Random Forest, AdaBoost, Gradient Boosting, XGBoost showed varying degrees of performance, with accuracies ranging from 84.93% to 92.86% ; **Image Dataset (Alzheimer's MRI):** *SVM:* accuracy: 84.49%, precision : 91.72%, recall : 64.53%, F1-score : 67.99%. |
| 6 | Youxiang Zhu et. al., [7] | Deep Learning | ImageNet for MobileNet, AudioSet for YAMNet, fine-tuned models | **Text-based Models:** *BERT Base: accuracy :* 80.83% ; *BERT Large: accuracy :* 81.67% ; *Longformer : accuracy :* 82.08%. **Audio-based Models:** *MobileNet:* accuracy: 59.00% without pre-training, 58.8% with pre-training; *YAMNet:* accuracy : 66.20%. **Multi-modal Models:** *Dual BERT (Concat Fusion):* accuracy : 82.92% ; *Dual BERT (Add Fusion):* accuracy : 82.08% ; *YAMNet + BERT Base:* accuracy : 82.50% ; **Multi-task Transfer Learning:** *BERT Base (without pre-training):* accuracy of 78.75%, regression RMSE of 4.70 ; *BERT Base (with pre-training):* accuracy : 80.83%, a regression RMSE of 4.15. |
| 7 | Daniel P. Kumpik et. al., [8] | Deep Learning | ADReSS subset of speech transcripts | *Diagnostic prediction* accuracy of 3%, *ADReSS* accuracy : 97%, *CUBOId* conversations produced mixed performance, yielding an accuracy of 64% better than chance at both the |

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| | | | | conversation (50%) and sub-conversation (25%) level |
| 8 | Madhav Acharya et. al., [9] | Deep Learning | EEG signal public dataset | *Three-Class Classification (AD, FD, Control):* Accuracy: Approximately 95.70% ; *Binary Classifications: AD vs. FD:* Accuracy: Exceeds 98%, *FD vs. Control:* Accuracy: Exceeds 98% |
| 9 | Gazi Tanbhir et. al., [10] | Deep Learning | Federated Learning (FL), Quantum Key Distribution (QKD)-Inspired Encryption, CNN Architecture, MRI data | *Baseline Model (Without Encryption):* Accuracy: 77.77% , Loss: 5.0011 ; *Encrypted Model (With QKD-Based Encryption):* Accuracy: 77.77% (Identical to baseline), Loss: 4.9535 (Slight improvement) |
| 10 | Shivani Ranjan et. al., [11] | Deep Learning | EEG Source Localization | **BrainLat Dataset:** 94.17% accuracy using *DenseNet201* , **IITD-AIIA Dataset:** 77.72% accuracy using *DenseNet201*, CWT outperformed STFT (91.71% accuracy) |
| 11 | Marko Niemel et. al., [12] | Machine Learning | Acoustic Speech | *Ridge model:* 87.8% accuracy, *EMLM model:* 85.3% and 79.2% accuracy |
| 12 | Ramyasri M M et. al.,[13] | Machine Learning | Longitudinal MRI Data from the Open Access Series of Imaging Studies (OASIS) dataset | *Random Forest:* accuracy: 0.99, *Decision Tree*: accuracy : 0.95 *KNN:* accuracy 0.49 *GaussianNb:* accuracy 0.99, *SVM:* accuracy 0.99 *AdaBoost:* accuracy : 0.99 |
| 13 | S Gupta, J Parikh et. al., [14] | Machine Learning | The Open Access Series of Imaging Studies (OASIS) database, Alzheimer's dataset | *Naïve Bayes:* accuracy 95%, precision: 98%, recall : 93% , F1-score:95% |
| 14 | PH Kachare et.al., [15] | STEADYNet: Spatiotemporal EEG Analysis for Dementia Detection Using CNN | Electroencephalogram (EEG) signal | *STEADYNet* accuracies of 99.29%, 99.65%, 92.25% for Alzheimer's disease, Mild cognitive impairment and frontotemporal dementia |
| 15 | Zerin Jahan et. al.,[16] | Machine Learning | Word embeddings , Sentence embeddings, Linguistic features, Preprocessing techniques | *SVM:* Accuracy: 97.41, Precision: 97, Recall: 96, F1-score: 97; *KNN:* Accuracy: 98.70, Precision: 98, Recall: 98, F1-score: 99; *Random Forest :* Accuracy: 99.02, Precision: 99, Recall: 99, F1-score: 99; ANN: Val_loss: 2.39, Val_acc:98.71, Loss:2.39,Accuracy:98.70 |
| 16 | Jinkui Hao et. al., [17] | Deep Learning | Retinal Imaging Modalities, OCTA images | EOAD Detection: *Internal Dataset (ROAD-I)*: Accuracy: 88.85%, Precision: 88.62%, F1-score: 88.67%, Kappa: 0.7018, AUC: 0.9355 ; *External Dataset (ROAD-II)*: Accuracy: 81.76%, Precision: 84.29%, F1-score: 82.91%, Kappa: 0.5865, AUC: 0.9007, MCI Detection: *Internal Dataset (ROMCI-I)*: Accuracy: 84.87%, Precision: 85.06%, F1-score: 84.10%, Kappa: 0.6229, AUC: 0.8630 ; *External Dataset (ROMCI-II)*: Accuracy: 84.44%,Precision: 83.92%,F1-score: 83.39%,Kappa: 0.5489,AUC: 0.8037 |

Table 1 presents the various experiments conducted by authors on various modes of datasets and their performances. The accuracy parameters from each experiment has been collected and depicted in the Figure 1. The graph indicates that the experiment conducted on EEG mode using CNN has outperformed upto 99.29% of accuracy compared to other experiments.

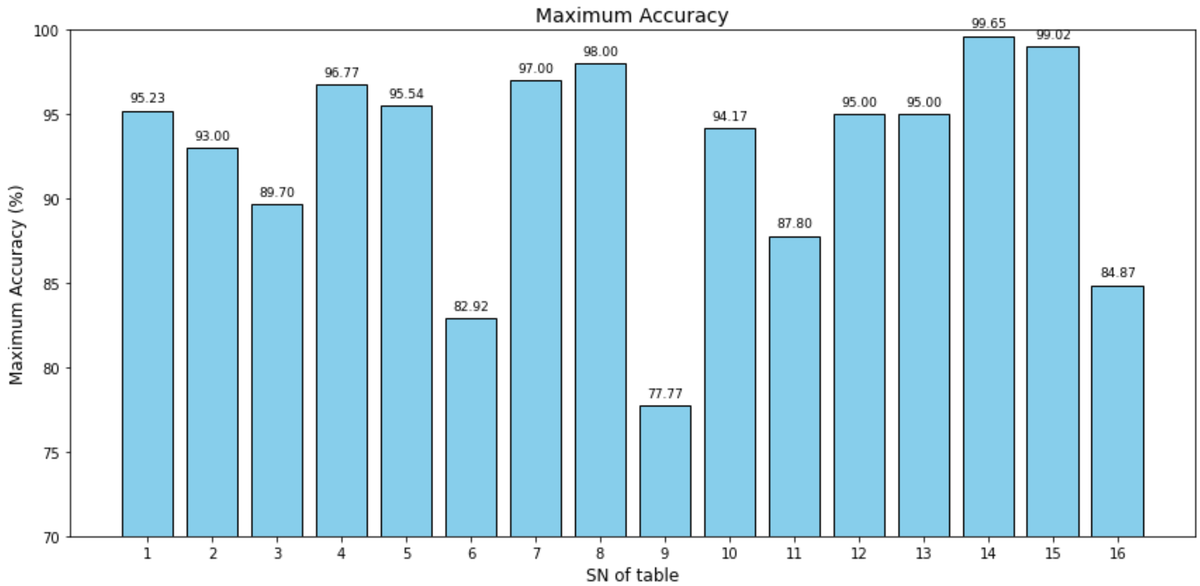


**Figure 1: Maximum accuracies of the models mention in Table 1**

## 4. Assistive solutions for dementia

The article [25] gives a summary of Intelligent Assistive Technology Devices (IATD) intended to help people with dementia with a particular emphasis on cognitive and communication impairments. The review observes that the majority of research has concentrated on topics like attention and social pragmatic communication and it summarizes the body of existing literature rather than emphasizing particular models or algorithms. It also emphasizes the fact that a large number of IATDs are still in the idea or prototype stage. The paper [26] reviews different IATD for dementia care. Findings from several experiments are summarized in the publication including one that used a fuzzy Adaptive Resonance Associate Map (fuzzy ARAM) neural network with an F1-score of 76.2% to identify mild cognitive impairment (MCI). Another study monitored night time wandering and evaluated fall hazards using motion, window and pressure sensors. The variety of strategies being investigated for efficient dementia care is demonstrated by these examples.

ToiletHelp is a system that helps people with dementia use the toilet on their own [27]. The system uses a modified ShuffleNet v2 model that has been adjusted to maintain spatial information and it incorporates a depth sensor (Orbec Astra) for privacy. A synthetic dataset was used to train the model then 21000 real world examples were used to refine it. It recognized user actions with 80% accuracy. Its efficacy was validated by a user centered evaluation including 14 caregivers and 33 end users. The study emphasizes ToiletHelps modular architecture which incorporates commercially available algorithms for real time performance without requiring a lot of data collecting.

A review and expert consultation were undertaken by the paper [28] in order to develop guidelines for the implementation of IATDs at various stages of dementia. Instead than concentrating on particular models or datasets the study reviewed the literature and collected opinions from five experts in dementia care. An infographic was updated by the experts to reflect more precise scheduling for the introduction of IATDs including earlier usage of medication dispensers and lifestyle monitoring. The redesigned infographic uses color coding to differentiate between technologies related to care and those focused on pleasure. The study highlights the significance of taking individual requirements into account when implementing Assistive Technologies for dementia care. The paper [29] proposes a technology that helps people with dementia use the toilet on their own. In order to protect user privacy it uses a 3D sensor (Orbbec Astra) to take depth maps. A rule based engine and CNNs then process the data to identify user activity. The paper [30] examines wearable technology for dementia care emphasizing important innovations such intelligent data analytics, adaptable interfaces and wearable context monitoring. Also discussed about the platforms like SMART4, CAREGIVERSPRO-MMD and DEM@CARE that employ wearable technology to track activities, assess health and send reminders the report summarizes the results of other research projects. To increase the use of wearable technology in dementia care the authors urge more study into affordable sensors and better data fusion. A pilot project that turned the Memory Treasury Hunt into a digital tool for people with dementia and mild cognitive impairment (MCI) is described by [31]. The project employed a cooperative and evidence based methodology by incorporating different stakeholders and senior users at every stage of development. A variety of techniques were used to collect input to evaluate the digital kits usability and make improvements. The study stresses teamwork and user centered design but it does not concentrate on any particular models or techniques.

An overview of AI integration into assistive technology (AT) in healthcare can be found in the paper[32]. The study analyzes themes, possibilities, difficulties and suggestions by synthesizing findings from 19 review articles using a standardized checklist. The study emphasizes AIs revolutionary potential in mobility, diagnostics and cognitive assistance enabling individualized solutions even though no particular models or algorithms are mentioned. It also covers issues like privacy issues, digital literacy and the requirement that AI systems be able to adjust to the needs of each user. The study highlights the rising financial investment in AI powered assistive technology as well as the necessity of overcoming obstacles including exorbitant development costs and legal concerns to guarantee wider use. The study analyzes themes, possibilities, difficulties and suggestions by synthesizing findings from 19 review articles using a standardized checklist. The study emphasizes AIs revolutionary potential in mobility, diagnostics and cognitive assistance, enabling individualized solutions even though no particular models or algorithms are mentioned. The design principles for Assistive Technology (AT) for people with disabilities are examined in the paper [33]. With a focus on user centered design, accessibility and the incorporation of emerging technologies the paper synthesizes interdisciplinary concepts to offer a paradigm for inclusive AT development. It emphasizes the value of teamwork and a comprehensive strategy to meet a range of user. The intention is to provide guidance for the development of AT that enhances the autonomy and quality of life of people with disabilities while also being functional and empowering. The factors impacting the adoption of wearable technologies in dementia care are examined in the paper [34]. In order to pinpoint user resistance issues including usability issues, privacy concerns and device complexity it synthesizes the body of existing literature. Simplified interfaces and customisable features are among the design advancements that are discussed in the article that are centered on user centric approaches. It highlights the value of stakeholder involvement and iterative design in order to improve wearable devices for dementia care. The results are intended to direct future studies to improve the efficacy and acceptance of wearable technology.

**Table 2: Various assistive solutions for dementia, modes and dataset involved**

| AUTHORS | Assistive solution | Modality / Model | Dataset |
|---|---|---|---|
| Sampson Addae et. al.,[26] | EEG and VR Integration, Smart Glasses, Sleep Monitoring Devices, IoT-Based Home Monitoring. | Sensor Technologies, Machine Learning and Deep Learning, Statistical Analysis, Federated Learning, | ADNI (Alzheimer's Disease Neuroimaging Initiative), NACC-UDS (National Alzheimer's Coordinating Center - Uniform Data Set), OASIS (Open Access Series of Imaging Studies), Dementia Bank (PITT Corpus) |
| Irene Ballester et. al., [27] | ToiletHelp | Depth Sensors, On-Device Processing, Multimodal Feedback, User-Centered Design | Participant Involvement, User-Centered Evaluation, Data Availability |
| Sima Ipakchian Askari et. al., [28] | Socially Assistive Robots (SARs), Lifestyle Monitoring Systems, Cognitive Stimulation Applications | Sensor-Based Monitoring, Mobile and Tablet Applications, Wearable Devices, Telehealth Platforms, Smart Home Technologies | Literature Review of Existing Studies, Expert Interviews and Evaluations, Infographic Development Based on Synthesized Data |
| Irene Ballester et. al., [29] | ToiletHelp System | Depth Sensor-Based Monitoring, On-Device Processing with Rule-Based Engine and Convolutional Neural Networks (CNNs), Multimodal User Interaction (Verbal and Visual Prompts) | Real-Life Evaluations with 20 Individuals with Dementia in Two Settings, Synthetic Data for Training Modules, Previously Collected Dataset for Person Tracking and Posture Classification |
| Po Yang et. al., [30] | Memory Support Systems, Cognitive Training Tools, Fall Detection and | Wearable Sensors, Mobile Applications, Cloud Computing Platforms, Artificial Intelligence | Literature Review Data, Case Studies and Pilot Projects, Publicly Available Datasets, Proprietary |

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|---|---|---|---|
| | Prevention Systems, Health Monitoring Devices, Emergency Alert Systems | Algorithms, Internet of Things (IoT) Integration | Datasets from Research Initiatives |
| Florence Meng-Soi Fong et. al., [7] | eMemory Kits | Digital Cognitive Training Tools | Mixed Methods Evaluation Data |
| Daniele Giansanti et. al., [8] | Smart Wheelchairs, Exoskeletons, Brain–Computer Interfaces, Cognitive Support Systems, AI-Powered Prosthetics, Autism Support Devices | Artificial Intelligence Algorithms, Machine Learning Models, Robotic Systems, Wearable Sensors, Mobile Applications | Systematic Literature Review, Review of Nineteen Studies |
| Andrew Paice et. al., [9] | User-Centered Assistive Technologies | User-Centered Design Methodologies | Exploratory Research Data |
| Hà Trang Phan et. al., [10] | Wearable Devices for Dementia Care | Wearable Technology | Systematic Review of Literature |
| Shakila Dada, et. al., [25] | Social Robots, Reminder Systems, Monitoring Systems | Context-Aware Computing, Artificial Intelligence (AI), Augmentative and Alternative Communication (AAC) | Systematic Review of Literature |

Table 2 depict the various assistive solutions made by involving datasets and computing models. This survey helps to understand the current developments in providing solutions to the dementia and combinations of various modes with computing models. The other possible combinations can be thought along with dataset preparations.

**Conclusion**

Dementia continues to pose significant challenges in healthcare both in diagnosis and daily care management. This survey explored the current landscape of dementia research by emphasizing the datasets, machine learning models and assistive technologies that contribute to early detection and patient support. Through comparative analysis of model performance and the integration of relevant datasets it is evident that data quality and algorithmic advancements play a crucial role in enhancing diagnostic accuracy. Also the assistive technologies ranging from cognitive support systems to sensor based monitoring demonstrate considerable promise in improving the quality of life for individuals living with dementia. However, a unified framework that combines robust models with real world applicability remains an area of ongoing research. Future directions should focus on personalized and ethically responsible AI driven systems by ensuring accessibility, interpretability and scalability. By bridging data science with compassionate care the path forward offers hope for more effective dementia management and meaningful patient engagement.

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